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Modelling uncertainty of vehicular emissions inventory: A case study of Ireland

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ABSTRACT

The vehicular emission modelling software COPERT is extensively used in generating emission levels for National Emissions Inventory in Europe and in some other countries internationally. This paper aims to study the uncertainties associated with emission estimates generated from COPERT(v5.1) outputs through sensitivity analysis of the model input parameters. The input parameters considered in this study are temperature, speed, relative humidity, trip length, and driving style (mileage share). Many of these parameters are not directly measured or country-wide average values are investigated in this study. The uncertainties of the emission estimates were obtained through varying the parameter values, within realistic limits, either individually or considering factor interactions by varying two or more parameters simultaneously. The uncertainties of the emission estimates of certain pollutants (CO, VOC and NMVOC) can be significant from −58% to +76%. Some gases, such as CO_2 show almost no sensitivity to input parameter variations. The results indicate that the COPERT outputs are most sensitive to variations in trip length and speed, both of which are not directly measured. Considering the percentage of urban driving share has a huge effect on the national emission estimates, inventories were separately prepared for the Greater Dublin Area (GDA), the largest urban area of Ireland with highest population and vehicle densities. GDA has 48% and 50.37% shares of CO_2 and NOx emissions respectively, compared to the national levels. The consequence of over- or underestimation of emission inventories for Ireland was calculated to be approximately +/− €45million. Considering the major implications of NEI for climate change and other related impacts it is crucial to report the pollutant emission levels appropriately stating uncertainty levels. The findings of this study provide national experts with a methodology to estimate uncertainties of COPERT outputs and to identify the key sources of these uncertainties where policy and emission reduction strategies should be targeted.

1. Introduction

Transport is a major air polluting which accounts for 23.2% of the overall greenhouse gas emissions in Europe (Eurostat, 2014). In Ireland, the emission share from transport is about 20% (EPA, 2017). Over the past 15 years, the number of cars in Ireland has increased by 43% (CSO, 2016a; DTTAS, 2016a,b). Also, the transport sector is the largest energy-consuming sector in Ireland, with a share of 42% in 2015 (SEAI, 2015). Road transport is responsible for the emissions of various regulated and unregulated pollutants (Gkatzoflias et al., 2012). Major parts of carbon monoxide (CO) and carbon dioxide (CO_2) emissions result from passenger cars (Fameli and Assimakopoulos, 2015). The emissions from on-road vehicles account for 95.8% of the overall transport emissions in Ireland (EPA, 2017). The impact of air pollution is higher in urban areas due to higher vehicle density and in urban areas, the main source of air pollution is road transportation. A large percentage of urban populations are exposed to air pollution which is higher than the safe air quality guidelines recommended by European Union (EU) and WHO (WHO, 2013).

Several targets are now set to reduce the emissions and its subsequent impacts on environment and health. National Emission Inventory (NEI) is the main component of air quality management and used in air pollution control programme, emission projections, emission prevention and control measures, quantification of actual emissions, development of policies to prevent and control emissions and environmental impact assessment (ACAP, 2007; Souza

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et al., 2013; USEPA, 2017; Yan et al., 2014). In NEI, emission levels from transport sector are affected by various factors associated with the road (road surface condition, gradient, pavement type etc.), vehicle (engine size, fuel type, technology class etc.), environment (relative humidity, temperature etc.) and traffic (speed, acceleration etc.) (Demir et al., 2011). All vehicular emissions models used to calculate emission levels for NEI utilise these factors as input variables in some form. But models are imperfect abstractions of reality and due to lack of availability of precise input data, all outputs are subject to imprecision and uncertainty (Loucks et al., 2005). The rarity of the direct analytical relationship between the input factors and emission levels, unrestricted use of assumed values in the absence of measured input such as real average speed and inability to consider significant spatial and temporal variations in all inputs the calculated emission levels inherit significant uncertainty. The quality of the inventory can significantly be improved by using detailed input data and reducing any uncertainty (Kouridis et al., 2010). Uncertainty in emissions estimates has been assessed by Kioutsioukis et al. (2004), Notte et al. (2018) and Saikawa et al. (2017) and it is recommended by the European Commission in its National Emissions Ceilings Directive and by Intergovernmental Panel on Climate Change in its guidelines for National Greenhouse Gas Inventories that NEI reports must include information on uncertainties (EU, 2016; Eggleston et al., 2006).

Sensitivity analysis, on the other hand, helps to build confidence in the model by studying the uncertainties that are often associated with parameters in models (Yao et al., 2014). A sensitivity analysis combined with uncertainty analysis can help to understand if the current state of knowledge about the input data and related uncertainties is enough to take the decision and helps in identifying factors for which data or parameters need resource allocation to achieve the desired level of confidence on the results (Kioutsioukis et al., 2004). Several researchers have carried out a sensitivity analysis of emission modelling parameters for the following software: MOVES (Choi et al., 2010; Yao et al., 2014), Mobile 6.2 (Garcia et al., 2013) and MicroFacPM (Singh et al., 2012).

The most popular vehicular emission modelling software used in calculating NEI in EU is COPERT (COmputer Programme to calculate Emissions from Road Transport) which was developed for use by national experts to calculate road transport emissions to be included in official annual national inventories, with the support from European Environment Agency (EEA) (2018). COPERT is used by 22 European member states for official submission of road transport inventories (Kioutsioukis et al., 2004). Consequently, COPERT has been used by several researchers in Ireland (Alam et al., 2018a; Alam et al., 2018b; Brady and O'Mahony, 2011; Caulfield, 2009; Dey et al., 2017; Doorley et al., 2015) and researches in other countries (Fameli and Assimakopoulos, 2015; Borge et al., 2012; Du et al., 2017; Lv et al., 2019; Ong et al., 2011; Pouliot et al., 2012; Song et al., 2016).

COPERT requires detailed meteorological, activity and fleet data as input. However, the spatial and temporal variability of recorded meteorological data cannot be considered in COPERT. Though fleet composition can be accurately obtained from the national database, activity related data like average trip length or mileage share are not measured. However, the inventory reports often do not give insight about the input data and assumptions (EPA, 2017) and little to no information on the uncertainty of emission estimation. As discussed previously this information is of utmost importance for NEI and there exist very few studies investigating the sensitivity of inputs or uncertainty of COPERT outputs. Vanhulsel et al. (2014) examined the pitfalls in calculations of road transport emission inventories and projections in Belgium by studying effects of speed profiles, trip lengths, hot emission factors and cold start emission factors on the emission levels. The authors used the E-Motion Road model which is based on the COPERT 4 methodology. In another study with a different objective, Fameli and Assimakopoulos (2015) calculated an emissions inventory for Greece and Attica (Greater Athens Area) by evaluating scenario-based analysis varying important input parameter such as temperature, speed, mileage share, trip length. Furthermore, a direct physical or analytical relationship between input parameters and emission estimates are not available due to the complexity of the calculation and use of emission factors in COPERT modelling methodology (EMISIA, 2017). Hence, it is essential to perform an in-depth sensitivity and uncertainty analysis of emission levels calculated using COPERT for individual countries.

In this paper, a detailed sensitivity and uncertainty analysis of COPERT5 is carried out for emission estimates from road transport (passenger cars) for Ireland. In the study, the emission levels of CO_2, CO, NOx, $PM_{2.5}$, PM_{10}, VOC, NMVOC, and N_2O were calculated using COPERT5, the most updated version of the software (EMISIA, 2017), and have been reported for varying temperature, average speed, relative humidity, driving style share and average trip length. In this analysis, an exhaustive set of all parameters which lack precision has been considered and sensitivity analysis has been performed by considering individual effects along with factor interaction effects. As for the uncertainty analysis of outcome emission levels, probabilistic statistical modelling was carried. In addition, emission levels of GDA which consists of about 40% of Ireland's population (CSO, 2011) and 50% of total passenger cars present in Ireland (SIMI, 2015) were calculated. The more densely populated areas are mainly located within GDA (CSO, 2016b).

The findings of this study provide critical information in terms of possible levels of uncertainty associated with reported emission levels in NEI and the sensitivity of these variations to the input data and assumptions. The variations in damage costs of emissions as a result of variation in emissions estimates were calculated in this paper. This gives an example of the consequence of over- or underestimation of emission inventories on its applications which for Ireland was approximately €40million. The implications of the results are of importance to policy makers for emission prevention and control measures and the methodology is an essential tool to environmentalists for quantification of actual emission levels, emission projections and to both for environmental impact assessment and reporting of emission inventories.

2. Data description

The data used in this study and their respective sources have been described in this section. The extent of availability and ranges of their variability have also been described. Table 1 shows the necessary input parameters for COPERT5 and their required level of disaggregation along with their extent of availability and sources. Input data like fuel/energy consumption and kilometres travelled can be derived from National Car Testing database. The fleet configuration can be accurately obtained from the national vehicle registration database. Information on temperature, relative humidity are recorded in monitoring stations across the country but a single average value is used as input for the entire country. Parameters, such as trip length (average), speed (average), and driving style (mileage share) are not measured at any level of detail and assumed values are used which can vary significantly.

The monthly average (spatial average of all monitoring stations) minimum and maximum temperatures are presented in Fig. 1. The mode (the most frequently occurring data) of the daily minimum and maximum temperature gaps are also shown in Fig. 1. Similarly, monthly average relative humidity and mode of the monthly average relative humidity recorded from all the monitoring stations are shown in Fig. 2.

Table 1
COPERT5 input data, their sources and their level of availability in Ireland.

Input data	Required level	Source	Measured/not measured
Fuel consumption (TJ)	Total for each fuel type	Sustainable Energy Authority of Ireland (SEAI, 2016)	Available
Fleet configuration	Disaggregated to each fuel-engine size- technology combination	Motorstats: The official statistics of the Irish Motor Industry (SIMI, 2016). Department of Transport, Tourism and Sport (DTTAS, 2016a,b).	Available
Trip length (km)	Trip length for the vehicle type under calculation	National Travel Survey (CSO, 2014a,b)	Yearly average reported
Temperature (C)	Monthly minimum and maximum temperature	MET Eireann: The Irish Meteorological Service Online (2016a,b)	Measured at monitoring stations
Relative Humidity (%)	Monthly humidity	MET Eireann: The Irish Meteorological Service Online (2016a,b) World Weather and Climate Information (2016)	Measured at monitoring stations
Driving share (%)	Disaggregated to Urban, Rural, Highway	Brady and O'Mahony (2011)	Not measured
Average speed (kmph)	Disaggregated to Urban, Rural, Highway	Road Safety Authority (2015)	Average free speed measured
Average annual mileage (km)	Disaggregated to each fuel- engine size-technology combination	CSO (2014a,b) SEAI (2013)	Measured

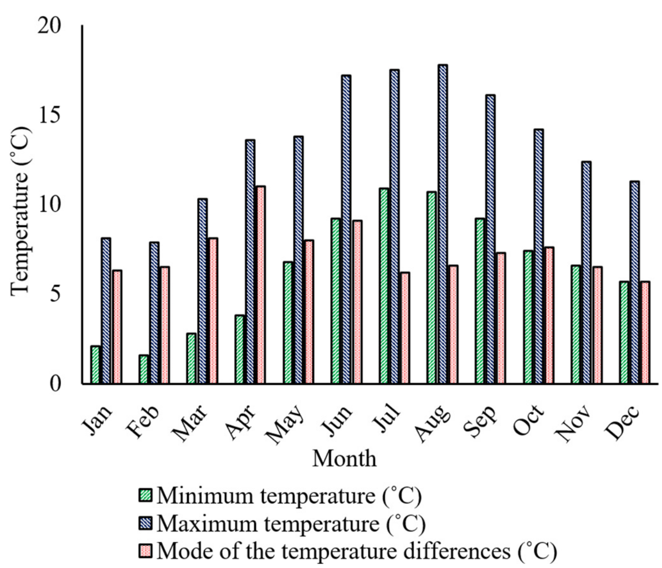

Fig. 1. Monthly average minimum, maximum and mode of the temperature differences at the base scenario.

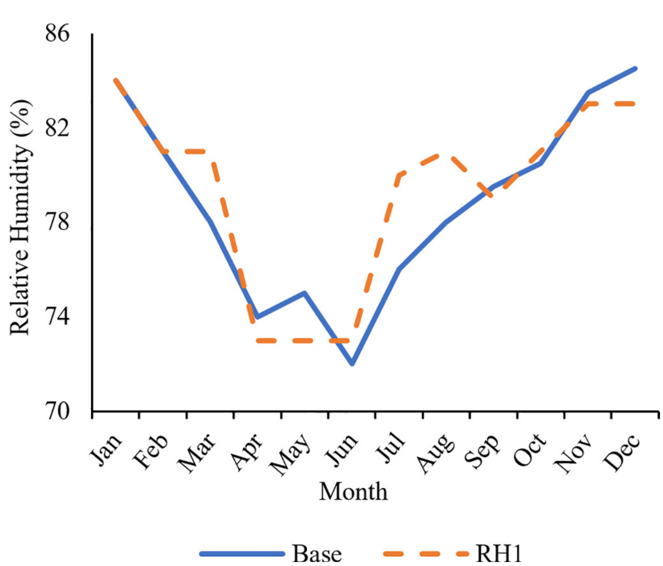

Fig. 2. Monthly average relative humidity (%) at the base scenario.

The fleet data are mainly extracted from the Society of Irish Motor Industry (SIMI, 2016) and DTTAS (2016a,b). The detailed division of fleet data with respect to engine classes i.e. Small (<1.4 L), medium (1.4–2.0 L) and large (>2.0 L), fuel type and technology classes (Euro 1, Euro 2 etc.) have been shown in Fig. 3.

For diesel cars, the medium sized engines are significantly higher in number than other engine sizes. Mileage share for the base case was assumed to be 16%, 8%, 76% for urban, rural and highway for GDA and the same shares for Ireland is taken as 30%, 50%, 20% respectively. These values were taken from the previous research carried out in Ireland (Brady and O'Mahony, 2011). The average urban driving speed for the base case was taken as 40 kmph, for rural as 60 kmph and highway as 100 kmph.

3. Methodology

This section presents the basic concepts of the COPERT5 model in estimating emission levels resulting from road transport, the methodology followed in developing national inventory using COPERT5 and in designing scenarios to capture the effect of possible variation of input parameters on emission levels.

3.1. COPERT algorithm

Depending on the extent of data availability, three different approaches can be used to calculate emissions (EEA, 2016). The methods are named as Tier 1, Tier 2 and Tier 3 approach. COPERT5 follows the Tier 3 approach which uses a combination of firm technical data, such as, EFs and detailed activity corresponding to each technology class. COPERT5 uses the improved methodology in terms of updated NO_X emission factors for diesel passenger cars and light commercial vehicles. The following set of equations are used to calculate the total emissions in the COPERT (Ntziachristos and Samaras, 2018),

$$E_{total} = E_{hot} + E_{cold} \quad (1)$$

where, E_{total} is the total emissions of a pollutant; E_{hot} is the hot exhaust emissions that occur when the engine and emission control system reach their typical operating temperature and E_{cold} is the cold start emissions discharged during transient thermal engine operation, i.e. when engines and catalysts are not fully warmed up. The hot exhaust emission is calculated using the following equation,

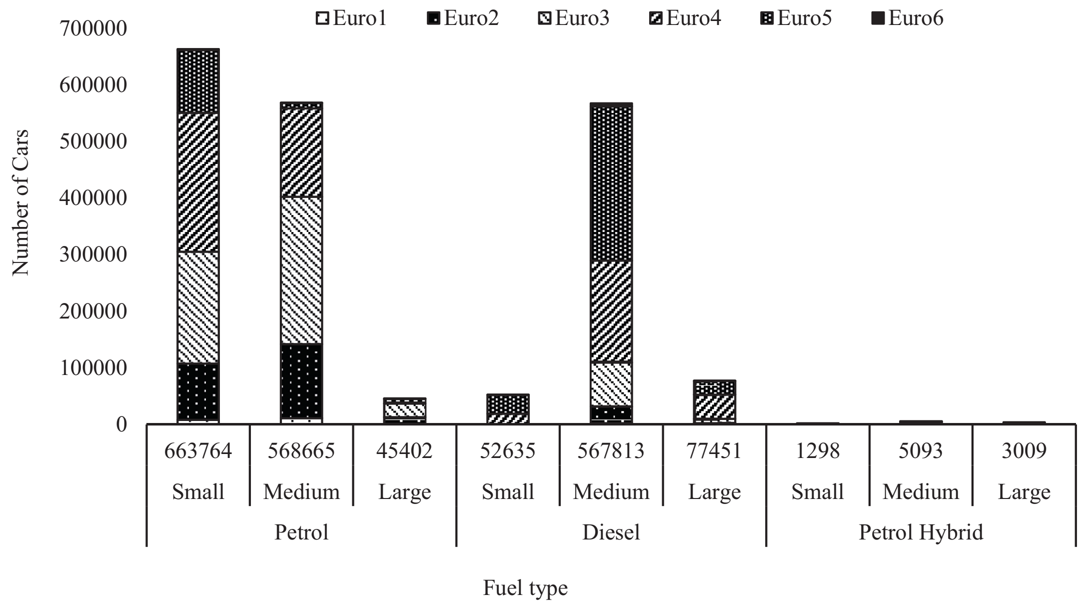

Fig. 3. Passenger car fleet composition by fuel type, engine size, and technology class in 2015.

$$E_{hot;p,t,r} = N_t * M_{t,r} * EF_{hot;p,t,r} \tag{2}$$

where, $E_{hot;p,t,r}$ is the hot exhaust emissions of the pollutant p, produced in the period concerned by vehicles of technology t driven on roads of type r; N_t is the number of vehicles of technology t in the period concerned; $M_{t,r}$ is the mileage per vehicle driven on roads of type r by vehicles of technology t; $EF_{hot;p,t,r}$ is the EF for pollutant p, relevant for the vehicle technology t, operated on roads of type r. The following equation is used in COPERT to calculate hot EFs,

$$EF_{hot;p,t,r} = \left(\alpha * S^2 + \Phi * S + \gamma + \frac{\delta}{V}\right) + (\varepsilon * S + \zeta * S + \eta) * (1 - RF) \tag{3}$$

where, α, Φ, γ, δ, ε, ζ, and η are regression coefficients and therefore, COPERT uses a set of predetermined set of these parameters depending on pollutant type, vehicle technology class, fuel type and road type. As can be seen in equation (3), the hot EFs are speed (S) dependent and need to be defined by the user. The equation also used a Reduction Factor (RF) which is applied where necessary. Cold-start emissions are introduced into the calculation as additional emissions per km using the following formula,

$$E_{cold;p,t} = \beta_{p,t} * N_t * M_t * EF_{hot;p,t} * \left(e^{cold} \Big/ e^{hot}_{p,t} - 1\right) \tag{4}$$

where, $E_{cold;p,t}$ is the cold-start emissions of pollutant p (for the reference year), produced by vehicle technology t; $\beta_{p,t}$ is the fraction of mileage driven with a cold engine or the catalyst operated below the light-off temperature for pollutant p and vehicle technology t; M_t is total mileage per vehicle in vehicle technology t; $e^{cold}/e^{hot}|_{p,t}$ is cold/hot emission quotient for pollutant p and vehicles of technology class t. The parameter $\beta_{p,t}$ is calculated based on trip length and ambient temperature. For petrol vehicles, $e^{cold}/e^{hot}|_{p,t}$ is calculated based on speed (S) and ambient temperature (t_a) using the following equation,

$$e^{cold} \Big/ e^{hot} = A * S + B * t_a + C \tag{5}$$

A, B and C are regression coefficients and a set of values are predefined in COPERT specific to pollutant type, certain speed ranges, engine size. Whereas, for diesel vehicles, $e^{cold}/e^{hot}|_{p,t}$ is calculated using only temperature values.

3.2. National Emission Inventory, Ireland (2015)

In order to calculate emissions inventory, passenger car fleet data were extracted from SIMI (2016). Three fuel categories have been considered, petrol, diesel and petrol-hybrid. A petrol-hybrid vehicle uses both an internal combustion engine using gasoline and electric motor to power the vehicle. Fleet data were sorted into three engine classes, <1.4 L, 1.4–2.0 L, and 2.0 L. A detailed description of the fleet composition is shown in section 2. Average Annual Mileage (AAM) values for each engine size class varying from <900 cc to >3000 cc (with 100 cc interval) for each year from 2000 to 2011 for diesel and petrol passenger cars were obtained from SEAI (2013) database provided by the National Car Testing services. These mileages were grouped into the three engine categories listed in COPERT5. These AAMs for each class were then extrapolated using individual regression relationships to get the AAM for 2015 similar to Alam et al. (2015). The goodness of fit values of mileage estimates of diesel vehicles were not as good as petrol vehicles. In order to examine the effect of any inaccuracy in AAM consideration with disaggregated engine and fuel consideration, COPERT was also run for the base scenario with AAM aggregated over all the engine size and fuel types. Aggregated AAM of all the cars in 2015 was obtained in the same way, i.e. by extrapolating 12-year's (2000–2011) aggregated AAM data. This showed a good fit with an R^2 value of 0.969. As mentioned earlier, emissions were calculated using COPERT5 for eight pollutants (CO, CO_2, NO_X, $PM_{2.5}$, PM_{10}, VOC, NMVOC, and N_2O) in tonnes per year. Passenger car emissions inventory was then prepared for GDA which has the largest share of population and automobile density in Ireland. The fleet data for GDA were also extracted from the official statistics of the Irish Motor Industry (SIMI, 2016).

3.3. Sensitivity analysis

In order to test the sensitivity of the model outputs to the input

parameters and quantify the possible uncertainty associated with the model estimates, input parameters related to weather and activity were examined. Two approaches were taken to assess this. At first, those input parameters were varied individually following one factor at a time method. Then based on one factor at a time analysis, more sensitive parameters were identified and two and three factors were varied simultaneously to examine the impact of factor interaction on emission levels. The scenarios are described in the following sections.

3.3.1. One factor at a time

In this scenario, the effect of single factor variation on emission levels was assessed. The input parameters considered are temperature, relative humidity, average speed, mileage share, and average trip length. A summary of the designed scenarios has been shown in Table 2. The details of the base scenario, designed scenarios and the approach followed to design the scenarios are described later in the following subsections.

- *Temperature (T):* COPERT requires monthly minimum and maximum temperatures for emission calculation. While calculating the emission levels for a whole country, the average of the recorded monthly maximum and minimum temperatures of all the stations are considered. But this may result in under- or over-estimation of emissions if some parts of a country experience significantly higher or lower temperature compared to other areas. To examine the level of variability in emission estimates as a result of temperature variations, three scenarios were designed in addition to the base scenario which presents the emission levels in 2015 taking temperatures as monthly averages of all the stations. The scenarios were designed such that the possible variation is captured. The scenarios were designed by taking into account the extreme minimum and extreme maximum recorded temperature of all the stations and daily temperature gaps between minimum and maximum. The mode of daily temperature gaps was considered to reflect the most occurring variation of daily temperature. It may be more realistic to take into account the gap between the minimum and maximum temperature in calculating the monthly minimum and monthly maximum which represents for a whole country. The designed temperature scenarios are described as follows,

  Temperature scenario 1 (T1),

$$T_{i,\min} = \{T_i\}_{\min} \tag{6}$$

$$T_{i,\max} = \{T_i\}_{\max} \tag{7}$$

  i = Month, i.e. Jan, Feb, Mar … Nov, and Dec.
  $T_{i,min}$ = Minimum temperature for emission calculation in month i.
  $T_{i,max}$ = Maximum temperature for emission calculation in month i.
  $\{T_i\}_{min}$ = Minimum of all the recorded temperatures at the monitoring stations in month i.
  $\{T_i\}_{max}$ = Maximum of all the recorded temperatures at the monitoring stations in month i.

  Temperature scenario 2 (T2),

$$T_{i,\min} = \{T_i\}_{\min} \tag{8}$$

$$T_{i,\max} = \{T_i\}_{\min} + d_{i,\mathrm{mode}} \tag{9}$$

$d_{i,mode}$ = Mode of the temperature gaps (shown in Fig. 1) between maximum and minimum in month i.

  Temperature scenario 3 (T3),

$$T_{i,min} = \{T_i\}_{max} - d_{i,mode} \tag{10}$$

$$T_{i,max} = \{T_i\}_{max} \tag{11}$$

- Relative Humidity (RH): Apart from the base case RH values, which is the average monthly RH of all the monitoring stations, another RH scenario was considered taking the mode of the monthly RH of all the monitoring stations.
- Speed (S): COPERT requires average speeds in urban, rural and highway driving conditions. Speed information for these categories is not precisely found. Speed is one of the major parameters influencing vehicular emissions, therefore, it is very important to see the possible variation in speed. In this study, the base scenario considers average speed for urban, rural, and highway as 40 kmph, 60 kmph, and 100 kmph respectively (Road Safety Authority, 2015; Alam et al., 2015). These speed

Table 2
Summary of the designed scenarios.

Parameter	Base scenario	Description of the tested scenario
Temperature (T)	Monthly average minimum and maximum	-T1: Extreme minimum and extreme maximum -T2: Extreme minimum among recorded temperatures as monthly minimum and extreme minimum plus mode of the daily temperature variations in that month as monthly maximum -T3: Extreme maximum among recorded temperatures as monthly maximum and extreme maximum minus mode of the daily temperature variations in that month as monthly minimum
Relative Humidity (RH)	Monthly average	-RH1: Mode of the monthly relative humidity
Speed (S)	Average speeds on Urban(40), Rural(60), Highway(100)	-S1: Speed limits on Urban(50), Rural(80) and Highway(110) -S2: Average lower speeds on Urban(25), Rural(50) and Highway(80)
Mileage share (MS)	Urban:Rural:Highway as 30%:50%:20%	-MS1: Urban:Rural:Highway as 30%:40%:30% -MS2: Urban:Rural:Highway as 40%:40%:20% -MS3: Urban:Rural:Highway as 50%:40%:10%
Trip length (TL)	15.1 km	-TL1: 6.0 km -TL2: 9.1 km -TL3: 12.1 km -TL4: 18.1 km -TL5: 21.1 km -TL6: 24.2 km

values are taken based on the free speed survey. To see the level of variability two extreme conditions were tested, one scenario (S1) considers the posted speed limits on urban, rural and highways and the other scenario (S2) considers the lowest average speed under those driving conditions.

- Mileage Share (MS): Driving style or MS is another very important factor in emissions calculation as the operating speed, road characteristics, traffic densities and thereby the exhaust emissions are different on regional roads, local roads, national roads etc. In COPERT, mileage share information is required for urban, rural and highways. The base mileage shares were taken as 30%, 50% and 20% for urban, rural, and highway respectively. Three scenarios have been designed (see Table 2), to capture the variability, denoted as MS1, MS2, MS3. The scenarios are designed such that the sensitivity of emission to each driving mode can be studied by comparing the results which are presented separately for each driving mode.
- Trip Length (TL): It is required to provide the average trip length (km) in COPERT. A single average trip length value is considered for a country average trip length. This is likely to vary and is important to see the impact of trip length on emission levels. This will also help to identify those trips causing more emissions and thereby finding alternatives to replace those trips to reduce emission levels. The trip length for the base case was taken as 15.1 km (CSO, 2014a,b). Six scenarios (TL1, TL2, TL3, TL4, TL5, and TL6), as shown in Table 2, were considered by increasing and reducing the average base trip length by 20%.

3.3.2. Factor interaction

In this case, the effects of multi-factor variation on emission levels have been studied. Emissions were calculated by varying two or more factors simultaneously. The designed scenarios are described in the following subsections.

- Temperature-Relative Humidity: This scenario studied the impact of variability of the weather parameters, i.e. temperature and relative humidity COPERT5on emission levels. The emission variations were studied for these two sets of RH (base and RH1) values against four temperature scenarios described in section 3.3.1. (i.e. base, T1, T2, and T3). Therefore total 2×4 emission estimates were obtained.
- Urban Speed-Trip Length: It was found that emission levels are significantly sensitive to urban speed and trip length. Therefore, average urban speed and trip length were varied simultaneously to understand their interaction. In this scenario, a range of possible urban speeds and trip lengths were studied in terms of their impact on vehicular emissions. Based on the national travel survey data, a range of trip lengths varying from 5 to 19 km was evaluated against an urban speed range of 20–45 kmph.
- Urban Speed-Trip Length-Urban Driving Share: The results showed that rural and highway emissions increase or decrease by the same percentage if the rural and highway driving shares are changed by certain percentages. However, it was observed that urban emission discharge is more sensitive to urban mileage shares. Therefore, the speed and trip length combinations tested in the previous scenario were run for three additional urban driving shares, 20%, 40%, and 50%.

3.4. Uncertainty analysis

Uncertainty associated with COPERT5 outputs were modelled by identifying characteristics of probability distributions of the pollutant emissions. The emissions estimated from all the scenarios were plotted as a histogram and fitted to the most suitable probability distribution function. Therefore, the sources of uncertainties related to input parameters were taken into account. The goodness of fit was tested using Kolmogorov-Smirnov (K-S) test at 5% significance level.

4. Results and discussion

In this section, the findings of this study are presented and observations from the results have been discussed.

4.1. Current inventory for Ireland and GDA

The emissions for the year 2015 in Ireland and GDA are presented in this section. Table 3 shows the passenger car emission inventories of CO, CO_2, NOx, $PM_{2.5}$, PM_{10}, VOC, NMVOC and N_2O for GDA and Ireland as calculated using COPERT5.

CO_2 emissions in Ireland from private car alone in 2015 was 6.095 Mt. GDA shares 62.94%, 48.00%, 50.37%, 43.93%, 39.53%, 59.43%, 59.34%, 51.57% of overall Ireland's CO, CO_2, NO_X, $PM_{2.5}$, PM_{10}, VOC, NMVOC and N_2O emissions respectively. This indicates a higher impact of pollution on the GDA population than the rest of the country.

4.2. Effect of input parameters on emission

4.2.1. One factor at a time

4.2.1.1. Temperature scenario. Temperature is an important parameter in emission levels as it affects the cold start and evaporative emission factors. Evaporative emissions are non-exhaust hydrocarbon losses from the fuel system of the vehicle. The results obtained from the temperature scenario are presented in Fig. 4. The relationship between COPERT EFs and temperature depends on the β factor, used in equation (4) in calculating cold start emissions, which is negatively dependent on temperature (Ntziachristos and Samaras, 2018). The results show that when extreme temperatures are considered, the difference in emissions levels is not significant. The maximum difference was found as 0.8% for cold start PM emissions, though the difference in total emissions is 0.1%. The reason behind this can be the increase in cold start emission due to lower temperature is neutralised by the lower emissions when the maximum average temperature is higher than the base case. To capture the emissions behaviour with lower temperature and higher temperature, T2 and T3 were designed. T2 and T3 represent more realistic situations as the mode of the daily temperature gaps between lowest and highest temperatures are taken into consideration. From the emission values in Fig. 4, it is observed that levels for cold and evaporative emissions increase (especially for CO, PM, and VOC) when the average monthly

Table 3
Passenger car emissions inventory (2015) for GDA and Ireland.

	Emissions (tonnes)							
	CO	CO_2	NO_X	$PM_{2.5}$	PM10	VOC	NMVOC	N_2O
Ireland	35,558	6,095,743	13,765	772.46	1038.73	3057.99	2717.38	182.35
GDA	22,380	2,925,957	6934	339.34	410.61	1817.36	1612.49	94.04

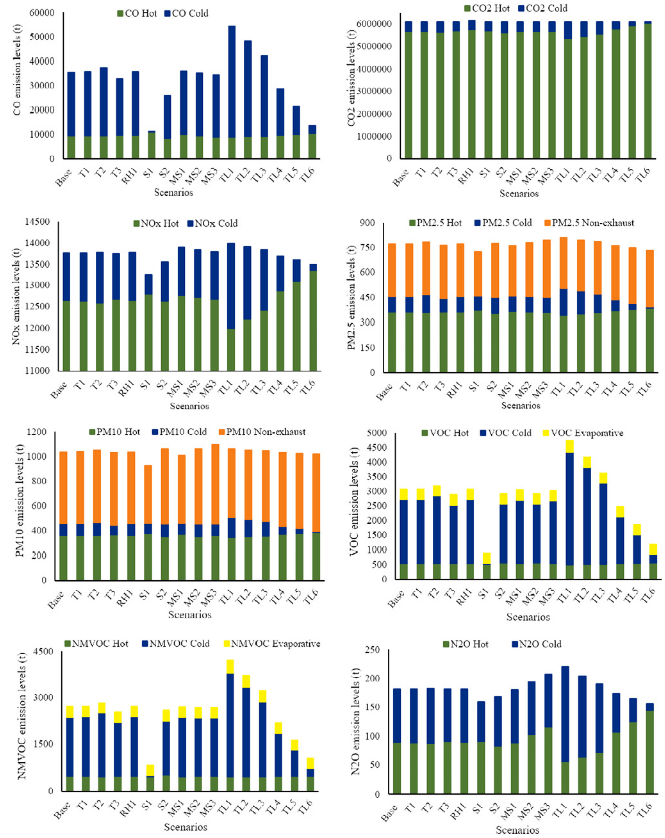

Fig. 4. Annual hot, cold, non-exhaust and evaporative emissions of CO, CO2, NOx, PM2.5, PM10, VOC, NMVOC, N2O for all scenarios presented in Table 2.

minimum and maximum temperatures are lower than that in the base scenario. The non-exhaust emissions which are the particulate (PM) emissions due to wear of brakes, tires, roads and re-suspended road dust, are also presented in Fig. 4. Non-exhaust emissions in the temperature scenarios do not show any notable variation.

The results obtained for T3 (Fig. 4), support the observation from T2 as the emission levels decrease when both the minimum and maximum monthly average temperature were taken to be higher than the base case temperatures. The reduction in cold start emissions for CO, NOx, $PM_{2.5}$, VOC, and NMVOC were 6.6%, 8.2%, 14%, 6.2% and 6.8% respectively from the base scenario.

There is no significant difference in emission levels when extreme monthly temperatures were taken which is because the increase in cold start emission levels due to lower temperature was balanced by the reduction in cold-start emissions due to higher maximum temperature compared to the base. However, when the minimum monthly temperatures were considered lower (T2) than the base temperature the cold start and evaporative emissions increase. Whereas, when the monthly average maximum temperatures were higher (T3) than the base, cold start and evaporative emission levels were lower. However, there were no significant differences in hot exhaust emissions in any of the scenarios, thus, it can be said that temperature mainly affects cold-start emission levels.

4.2.1.2. Relative humidity scenario. In COPERT EF calculations, relative humidity values are not directly taken into account. The results show that there is no significant change in emission estimates when modes of the RH values were taken instead of average values for the same monthly temperature values. RH is correlated to temperature; therefore, the impact of humidity can be better understood in the next section where the humidity and temperature are varied simultaneously.

4.2.1.3. Speed scenario. As mentioned in equation (3), the effect of speed on COPERT hot exhaust EFs is expressed by a polynomial equation and the parameters of the equation vary depending on pollutant type, driving mode, fuel type, engine size, and technology class. Also, cold start EFs are indirectly dependent on various speed ranges (Ntziachristos and Samaras, 2018). Therefore, it is very important to know how speed variations directly affect overall emission levels. It is observed that in S1 (Fig. 4) i.e. when the speed limits are taken as the average operating speeds, there is a significant reduction in emission levels in VOC (70.7%) followed by NMVOC (69.9%), CO (67.9%) and PM_{10} (10.6%). Whereas in S2 (Fig. 4), the differences in emission levels are not high except for CO (27.1%). In S1, emission levels were lower which is expected as the fuel consumption is lesser when the speed is higher. In S2, i.e. when the lower speed ranges were considered for all the driving modes, an overall reduction in emission levels was observed. It was identified that CO, NOx, $PM_{2.5}$, PM_{10}, VOC, NMVOC, N_2O emissions could be saved significantly if a higher speed equal to the speed limit could be maintained.

4.2.1.4. Mileage share scenario. In COPERT, mileage shares are used to divide the overall annual mileage as per driving mode and use in calculating EFs as shown in equation (2). Three mileage share scenarios have been designed to create the emissions inventory and observe the effect of each type of driving condition on emission levels. In Table 4, separate emission levels resulted from urban, rural and highway driving have been showed with the percentage

Table 4
Emission levels and changes in emission levels in mileage share scenarios.

Scenario	Driving mode share	Pollutants							
		CO	CO_2	NOx	$PM_{2.5}$	PM_{10}	VOC	NMVOC	N_2O
Base	Urban (t)	28587	$2.3*10^6$	5257	331	443	2649	2367	112
	Rural (t)	4272	$2.7*10^6$	5826	328	463	274	235	51
	Highway (t)	2699	$1.1*10^6$	2682	114	133	135	116	19
MS1	Urban (% change)	0	0	0	0	0	0	0	0
	Rural (% change)	−20	−20	−20	−20	−20	−18	−17	−20
	Highway (% change)	49	49	49	49	49	37	35	49
MS2	Urban (% change)	2	26	25	23	25	1	1	20
	Rural (% change)	−21	−21	−21	−21	−21	−18	−18	−21
	Highway (% change)	−1	−1	−1	−1	−1	−1	−31	−1
MS3	Urban (% change)	4	51	50	46	50	3	2	41
	Rural (% change)	−22	−21	−21	−21	−21	−19	−18	−21
	Highway (% change)	−51	−51	−51	−51	−51	−38	−36	−51

differences with respect to the base scenario.

The results indicate that with the increase in urban driving share leads to an increase in overall emission levels, especially for NOx, PM, and N_2O. Vanhulsel et al. (2014) and Fameli and Assimakopoulos (2015) also reported similar findings. CO_2 levels did not show considerable variation for the scenarios examined. It is observed that with 10% increase in urban driving share CO_2 emissions increase by 26% and NO_X and $PM_{2.5}$ increase by 25% and 23% respectively, whereas, with 10% reduction in rural share emissions reductions are around 20% for all the major air pollutants. Whereas 10% decrease in highway driving share results in about 50% lower emissions for CO, CO_2, PM, NO_X, and N_2O and 38% for VOC.

4.2.1.5. Trip length scenario. In COPERT, for the calculation of cold start emissions, the mean trip length is necessary. COPERT uses mean trip lengths provided by national experts decades ago (Ntziachristos and Samaras, 2018). In addition, the regression equation provided to express the relationship between trip length and EFs indicate an inverse relationship. In this paper, six trip lengths, of which three were taken by reducing the base trip lengths by 20%, 40%, and 60% and other three by increasing the trip lengths by the same percentages. The trip lengths examined were of 6.0 km, 9.1 km, 12.1 km, 18.1 km, and 24.2 km length. Table 5 presents total emissions from the base case and the percentage increase or decrease with the change in trip length. Fig. 4 shows cold start, hot exhaust, evaporative and non-exhaust emissions separately for all trip length scenarios.

It can be observed from the results that the emissions increases as the trip length decreases and vice versa. It was found that for lower trip lengths emission levels for CO, VOC, NMVOC increase by 52–55%. For the trip lengths varying from 18.1 to 24.2 km, the possible emissions savings range between 19 and 62% for CO, VOC, and NMVOC. This observation is in line with the findings of other researchers (Vanhulsel et al., 2014; Fameli and Assimakopoulos, 2015). There is no significant difference in CO_2 emissions was found, as it is mainly influenced by other factors such as fuel type, engine size etc. The fact that emission levels increase with the decrease in trip length for the same annual mileage indicates the possibility of significant emissions savings by replacing the shorter trips with walking or cycling.

Total emission levels of all the pollutants from all the scenarios have been presented in Fig. 5 by the box-whisker plot to see the range of variations. The horizontal lines present the minimum and maximum values and the red line inside the box shows the median. The black horizontal lines above and below the box present the minimum and maximum values. The figures show that there are significant variations in emission levels due to possible variation in input parameters.

Table 5
Base case emission levels and percentage difference in emission levels for trip length scenarios.

Pollutant	Trip length(km)						
	15.1	6.0	9.1	12.1	18.1	21.1	24.2
	Emission level (t)	Percentage difference from the base (%)					
CO	35,558	53	36	18	−19	−39	−61
CO_2	6,095,743	0	0	0	0	0	0
NOx	13,765	2	1	0.6	−0.6	−1	−2
$PM_{2.5}$	772	5	3	2	−2	−3	−5
PM_{10}	1039	2	1	0.6	−0.7	−1	−2
VOC	3058	55	37	19	−19	−40	−62
NMVOC	2717	55	37	19	−19	−40	−62
N_2O	182	21	12	4	−4	−9	−14

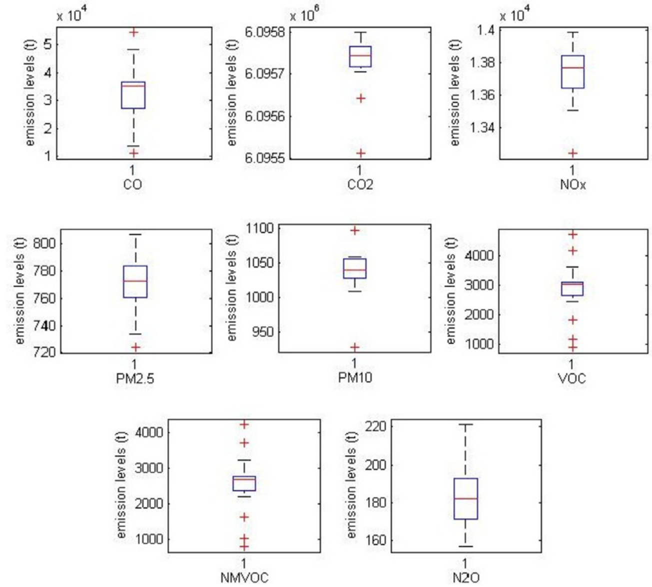

Fig. 5. The range of variability of emission levels of CO, CO_2, NOx, $PM_{2.5}$, PM_{10}, VOC, NMVOC and N_2O.

4.2.2. Factor interaction

4.2.2.1. Temperature-Relative Humidity. This section presents the emission variations against temperature and relative humidity scenarios as shown in Fig. 6. For CO_2, NOx, $PM_{2.5}$, PM_{10}, and N_2O, emissions are affected by T2. Therefore, it is observed that when both the lower and upper limit of average monthly temperature is lower than average, emission estimates of those pollutants are sensitive to RH. However, for T1 or T3, which considers relatively higher temperature ranges, the variation in emission levels are not significant. Also, there is no significant difference observed for CO, VOC, and NMVOC in any of the scenarios compared to the base case. This indicates that these pollutants are not sensitive to RH in the temperature ranges explored in this study. Although the emissions of some pollutants are sensitive to temperature and relative humidity, it depends largely on their interaction. More temperature and relative humidity scenarios can be examined for other countries which experience different weather conditions than Ireland.

4.2.2.2. Urban speed-trip length. Fig. 7 illustrates the 3D surface plots of CO, CO_2, NOx, $PM_{2.5}$, PM_{10}, VOC, NMVOC and N_2O emissions against the urban speed and trip length variations. All the pollutants follow a similar pattern as for individual parameter variations except NOx. For NOx, for lower speed in case of 20 and 25, emissions increase with increase with trip length but in case of speed 30 or higher, NOx emission levels increase with an increase in trip length. For CO_2, the effect of speed is least with respect to the speed variation. For CO, VOC, and NMVOC, emission levels decrease with increase in speed till 30 kmph and then start to increase. But as observed in S1, emissions start to decrease after that due to lower cold start emissions.

4.3. Uncertainty analysis

The probability density functions (PDF) of COPERT5 passenger car emissions outputs are presented in this section. In addition to the scenario results presented in the previous sections, emission levels at other urban shares (20%, 40%, and 50%) were run for the same trip length and urban share combinations as shown in Fig. 7. PDFs and the statistical parameters explaining the nature of the

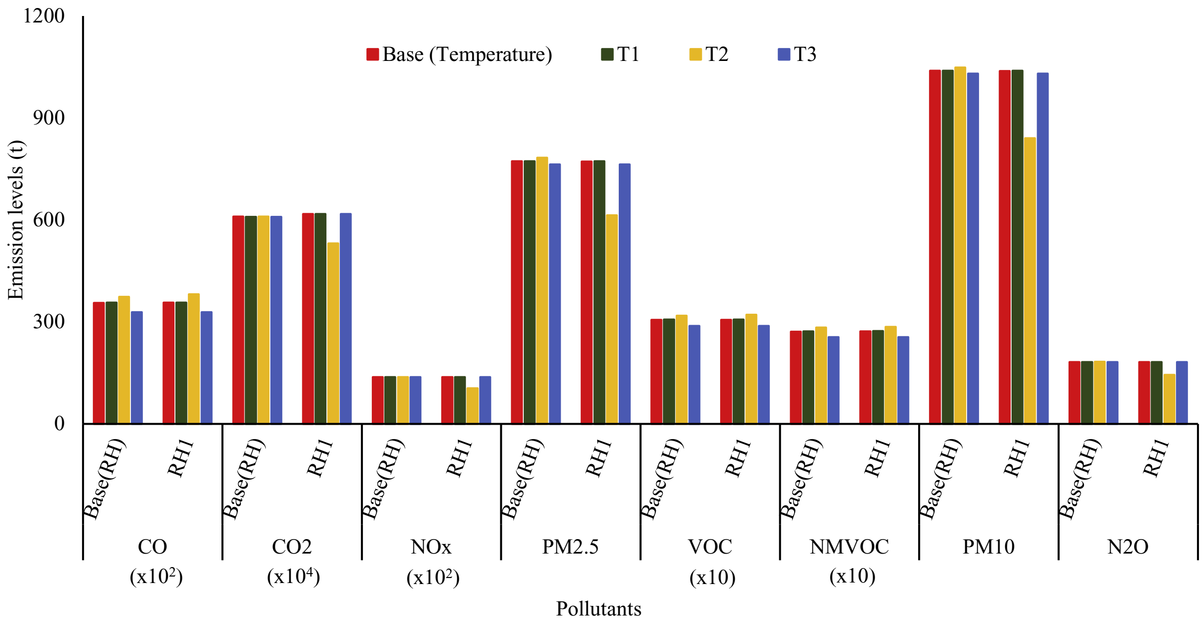

Fig. 6. Annual emission levels against Temperature and Relative humidity.

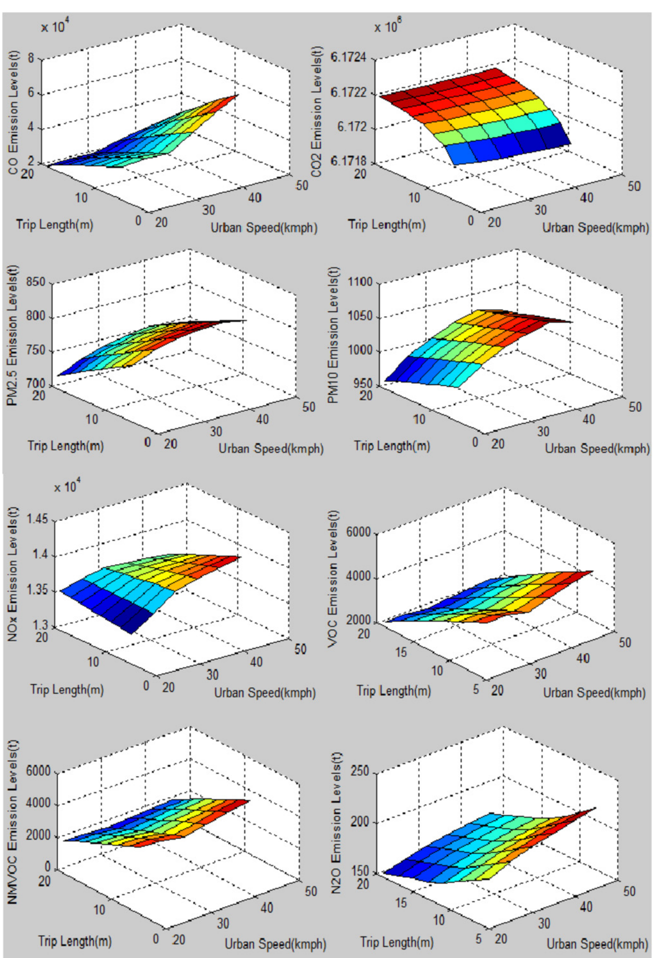

Fig. 7. 3D surface plots showing variations of annual emissions vs Trip Length and Urban Speed.

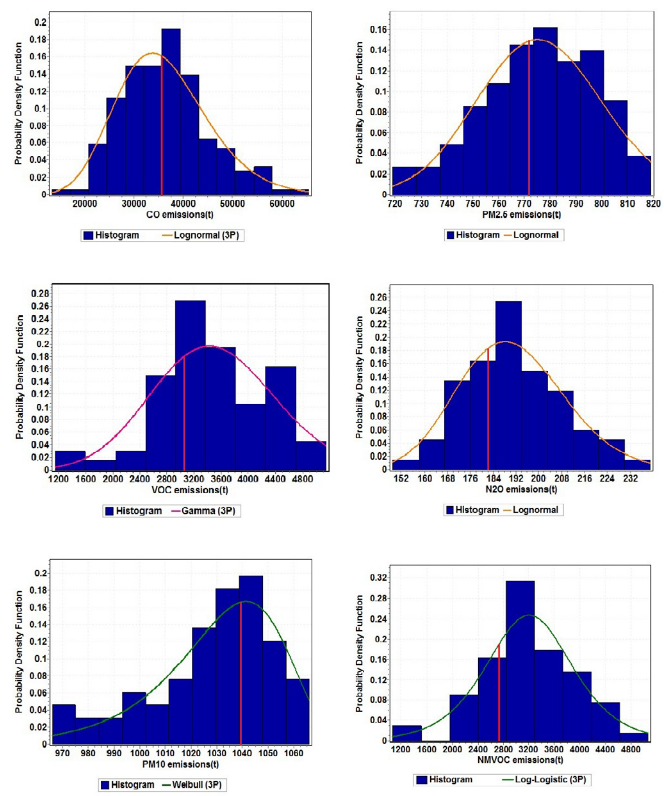

Fig. 8. Histograms and PDFs of annual passenger car emission levels. (Red line indicates the base case emission levels).

distributions are listed in Table 6. The coefficient of variation values presented in Table 6 indicates that CO_2, $PM_{2.5}$, NOx, and PM_{10} have a lower level of uncertainty in estimation with respect to input parameter variations in COPERT5. However, CO, VOC, NMVOC, and N_2O have a higher level of uncertainty. COPERT5.

The variability in emission levels of CO, VOC, NMVOC, N_2O are

Table 6
Statistical analysis results for each pollutant.

Pollutant	Sample Size	Mean	Standard deviation	Coefficient of variation	Skewness	Kurtosis	PDF
CO	187	34,205	9450	27.63	0.52	0.16	Lognormal(3P)
CO_2	171	6,161,406	65788	1.07	−1.06	0.14	Lognormal
NOx	186	13,747	300	2.18	−0.35	−0.29	Lognormal
$PM_{2.5}$	187	771	27	3.44	−0.20	−0.57	Lognormal
VOC	67	3253	893	27.44	−0.34	0.08	Gamma
NMVOC	67	2951	783	26.52	−0.17	−0.02	Log-Logistic
PM_{10}	67	1023	36	3.48	−0.52	0.61	Weibull
N_2O	67	186	19	10.19	0.35	−0.36	Lognormal

It has been statistically tested that the best-fitted PDFs of CO, CO_2, NOx, $PM_{2.5}$, and N_2O are lognormal distributions, VOC is gamma, NMVOC is log-logistic and PM_{10} is Weibull at 5% significance level. Fig. 8 illustrates the frequency histograms and PDFs for CO, $PM_{2.5}$, VOC, N_2O, PM_{10}, and NMVOC.

more than CO_2, NOx, PM with respect to the parameters evaluated in this study. The uncertainty associated with CO_2 emission estimates is nearly zero (−0.004–1.3%) with respect to the input parameter variation ranges, with a coefficient of variation value of 1.07. For NOx, $PM_{2.5}$ and PM_{10}, the uncertainties are higher than CO_2 with a coefficient of variation values 2.18, 3.44 and 3.48 respectively. Uncertainty in PM and NOx emission levels may deviate from the reported base case estimates by −24 to 3%. Whereas, CO, N_2O, VOC and NMVOC emission estimates from COPERT5 have significantly higher levels of uncertainty with respect to possible parameter variations, with the coefficient of variation ranging from 10.19 to 27.63. In reality, the emission levels of these pollutants might be much lower (up to 58% for CO, VOC, and NMVOC) or much higher (up to 79% for CO, VOC, and NMVOC) depending on the level of variation of the input parameters. For N_2O, the under- and overestimation lie between 21 and 31% respectively.

4.3.1. Cost implication

Greenhouse and non-greenhouse gases directly or indirectly cause damage to human health, crops, materials, plant and animal diversity. These damages caused by road transport emissions can be monetised using emission values (€ per tonne) (Table 7) reported by DTTAS (2016a,b) and in the handbook on external costs of transport (Ricardo-AEA, 2014). Based on the emission results from all the model runs, the damage costs in the base case and possible minimum and maximum have been reported in this section (Table 7). This gives information about the possible range of variation in damage costs depending on potential variations in emission estimates.

As can be observed from Table 7, the damage cost of $PM_{2.5}$ in urban areas is very high compared to damage costs in suburban and rural areas. The total cost of damage due to pollution from the PC fleet in Ireland was found to be €266.58 million in the base case with the highest cost associated with CO_2, followed by NOx and $PM_{2.5}$. However, the costs calculated for possible minimum and maximum scenarios show that there is the possibility of overestimation by €43.9 million or underestimation by €47.25 million in the base scenario. It is also to be noted that even though the per tonne damage cost of NOx is lesser than $PM_{2.5}$, the total cost is greater for NOx than $PM_{2.5}$. This indicates a higher level of NOx pollution from PC fleet.

4.4. Implication for theory, and practice

NEI data from all European countries are officially reported through the EEA utilising Eurostat database under the Convention on Long-Range Transboundary Air Pollution (CLRTAP) to the EMEP Programme (Co-operative Programme for Monitoring and Evaluation of the Long-Range Transmission of Air pollutants in Europe). The NEI for the Greenhouse gases is reported under the United Nations framework convention on climate change (UNFCCC). Considering the major implications of NEI for climate change and other related impacts it is crucial to report the pollutant emission levels accurately. COPERT has been developed with the support of EEA for use by national experts to estimate emissions from road transport to be included in official annual national inventories and consequently it is the most widely used emission modelling tool in EU and in some other countries outside EU. The flexibility of COPERT in utilising average values of input parameters such as temperature and assumed values of certain variables such as mileage share between urban, rural and highway driving conditions may prove to be a potential cause of variations in the estimated emission levels from the model. The model does not utilise the direct physical relationship between the aforementioned input parameters and emission levels using analytical forms which makes it complex to estimate how the changes in one parameter such as speed can impact the outcome emission levels. The study carried out in this paper is the first effort in exploring the sensitivity of the input parameters to COPERT and to estimate the uncertainty associated with the reported emission levels. This study will provide a critical tool to evaluate policies such as reduction of speed, changing driving patterns, reduction of average distance travelled

Table 7
Emissions and emissions values of pollutants in base, possible minimum and possible maximum cases.

Pollutants	Emissions values (€/t)	Base		Minimum		Maximum	
		Emissions (t)	Damage costs (mil€)	Emissions (t)	Damage costs (mil€)	Emissions (t)	Damage costs (€)
CO_2	13.22	6,095,743	80.59	6,095,514	80.58	6,172,219	81.60
PM_{10}	19143	1039	19.88	841	16.09	1060	20.29
NOx	5851	13,765	80.54	10,507	61.48	14,140	82.73
VOC	1438	3058	4.40	896	1.29	5124	7.37
NMVOC	1398	2717	3.80	818	1.14	4573	6.39
$PM_{2.5}$ (urban)	200239	331	66.26	267	53.41	536	107.24
$PM_{2.5}$ (suburban)	48779	114	5.54	88	4.28	105	5.12
$PM_{2.5}$ (rural)	16985	328	5.57	260	4.41	182	3.08
Total damage cost (mil€)		266.58		222.68		313.83	

in Ireland. Similar studies for other countries can be conducted to improve the understanding of the national inventories.

Additionally, rather than calculating country-wide emission inventories utilising average values of spatially varying parameters such as temperature, driving style or trip-lengths, it will be beneficial to focus on local areas or regions and then cumulatively report the aggregated emission levels. Furthermore, it is of utmost importance to provide ranges of emission levels for the different pollutants and to specify the values of input parameters used to calculate the emission inventories. More detailed reporting of NEI is essential to be adopted for future practice.

5. Conclusion

COPERT is one of the most popular road transport emissions modelling tools used in preparing emissions inventory in the EU and many other countries. This paper identifies the input parameters whose values are not measured or averages are considered in preparing emissions inventory for the whole country. Sensitivity analysis of those input parameters was carried out using COPERT5 through one factor at a time and factor interaction method by varying the input parameters within realistic limits. This paper further explores the uncertainties associated with COPERT outputs CO, CO_2, NOx, $PM_{2.5}$, PM_{10}, VOC, NMVOC and N_2O emission levels from passenger cars due to input parameter variations. In COPERT, emission levels of CO, NOx, VOC, NMVOC, and PM are calculated depending on speed, driving style (mileage share), trip length and temperature utilising EF. The EF values are calculated using regression analysis distinct for engine size, driving style etc. (Ntziachristos and Samaras, 2018). The emissions levels are not explicitly related with the input parameters examined in this paper through direct analytical relationship and therefore sensitivity analysis and uncertainty modelling exercises are essential to understand the extent of variations and sources of uncertainty in the outputs for a country and a region.

The results revealed that variability in emission levels of CO, VOC, NMVOC, N_2O are more than CO_2, NOx, PM with respect to the parameters evaluated in this study. The uncertainty associated with CO_2 emission estimates is nearly zero. However, uncertainty in PM and NOx emission levels are much higher and these levels can be over-reported based on actual values of the parameters such as speed, urban mileage share etc. In case CO, VOC, and NMVOC the over or underestimation is so significant (−58% to +79%) that providing assumed input values and uncertainty ranges are essential to be reported in NEI.

The results revealed that temperature variations is inversely related to CO, VOC, and NMVOC emission levels. Emission levels did not show any variation with respect to relative humidity variation. With the increase in trip length, the emission levels decrease and this is applicable to all the pollutants. It was found that with the increase in driving speed emission levels reduces. Decrease in speed ranges also showed a reduction in emission levels under the fleet composition tested in this study for Ireland and GDA. However, this relationship could be different in other countries with different fleet composition as speed EFs in COPERT is related to vehicle type, fuel type, and engine size as discussed in this paper earlier. Additionally, the results indicated that emission levels increase as urban driving share increases. Depending on the extent of variations in input parameters, the damage costs of air pollution caused by passenger cars in Ireland can be lower by 16% or higher by 18% than the base case in actuality. It is recommended that rather than reporting a single value of emission, a range of uncertainty for emission values should accompany the emission estimates to allow more credibility and transparency of the estimates.

The findings of this study not only identify the more influencing input parameters in COPERT5 outputs but also provides useful information to the users of COPERT5 by indicating the importance of measuring and appropriately reporting the assumed values the input variables. The results also suggest the accuracy of the emission estimates can be improved by calculating levels for smaller areas such as region-wide and summed up to represent the national inventory. More accurate and realistic assumptions of the input parameters may result in emission levels being significantly higher or lower than the current consideration leading to a better planning, modelling and policy making. The findings also inform about parameters (such as speed, trip length) which can be controlled to mitigate overall vehicular emissions.

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Appendix

List of Abbreviation

AAM: Average Annual Mileage
CLRTAP: Convention on Long-Range Transboundary Air Pollution
COPERT: Computer Programme to calculate Emissions from Road Transport
CSO: Central Statistics Office
CO: Carbon monoxide
CO_2: Carbon dioxide
DTTaS: Department of Transport, Tourism and Sport
EEA: European Environment Agency
EF: Emission Factor
EPA: Environmental Protection Agency
GDA: Greater Dublin Area
N_2O: Nitrous Oxide
NEI: National Emissions Inventory
NOx: Oxides of Nitrogen
NMVOC: Non-methane Volatile Organic Compound
PDF: Probability Density Function
PM: Particulate Matter
RH: Relative Humidity
RSA: Road Safety Authority
SEAI: Sustainable Energy Authority of Ireland
SIMI: The Society of the Irish Motor Industry
WHO: World Health Organisation
VOC: Volatile Organic Compound
UNFCCC: United Nations framework convention on climate change

List of Notation

$\{T_i\}_{max}$: Maximum of monthly recorded temperatures
$\{T_i\}_{min}$: Minimum of monthly recorded temperatures
$d_{i,mode}$: Mode of the monthly temperature gaps
$e^{cold} / e^{hot}|_{p,t}$: cold/hot emission quotient for pollutant p and vehicles of technology class t
E_{cold}: Cold start emissions
$E_{cold;p,t}$: Cold start emissions of pollutant p produced by vehicles of technology t
EF: Emission Factor
$EF_{hot;p,t,r}$: EF for pollutant p, relevant for the vehicle technology t on road type r
E_{hot}: Hot exhaust emissions
$E_{hot;p,t,r}$: Hot exhaust emissions of the pollutant p, technology t and road type r
E_{total}: Total emissions
I: Month
K-S: Kolmogorov-Smirnov
MS: Mileage Share
M_t: Mileage per vehicle in vehicles of technology t
$M_{t,r}$: Mileage per vehicle driven on road type r by vehicles of technology t
N_t: Number of vehicles of technology t
R^2: Coefficient of determination
RF: Reduction Factor
S: Speed
T: Temperature
$T_{i,max}$: Maximum monthly temperature
$T_{i,min}$: Minimum monthly temperature
TL: Trip Length
$\beta_{p,t}$: Fraction of mileage driven with a cold engine for pollutant p and vehicle technology t
t_a: Ambient temperature
A, B, C, α, Φ, η, γ, ζ, δ, ε: Regression coefficients